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Welding Defect Detection Using Machine Learning Model

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ABSTRACT: Benefits of AI are immense and we are already seeing this in many different fields. AI can help in dangerous environment, it can work 24x7 and it can be highly accurate. AI can be helpful in field of welding as well, it can help in monitoring of weld joints, it can detect welding defects and can be used round the clock. In this paper we have tried to show how we can take help of deep learning to do welding surface defect detection. We have used surface defect images of weld joints to train the state of the art YOLOv8s algorithm and then used that model to detect the defects in new set of images. Performance metrics scores of the model are good. Code and related files can be accessed at <https://github.com/aangatla/Welding-defect-detection-using-YOLOv8s>

KEYWORDS: Welding, Welding defect detection, YOLOv8, YOLO, You Only Look Once, AI, machine learning, deep learning, Computer vision.

I. INTRODUCTION

Welding holds great importance in field of mechanical engineering as without it many things which exist today cannot be imagined. It makes manufacturing complex parts easy. As welding is involved in many industries and is used very extensively so it becomes important that welding joints remain defect free. Failures due to welding defects have caused huge economic and human losses. In 1980, 123 people were killed as 'Alexander Kielland' a drilling rig capsized in North Sea and reason for this accident was a fatigue crack (*Alexander L. Kielland (Platform) - Wikipedia, n.d.*).

Welding defect is defined as flaw which compromises the usefulness of weld joint (*Welding Defect - Wikipedia, n.d.*). Here we should make a difference between flaw and defect, flaws are nothing more than imperfections in welding. Whether a flaw will become a defect or not depends on the place, size and location of flaw. The major reason behind the defects is following improper welding procedure (Mandal, 2017).

Welding defects are classified into two types, internal and external (surface) defects. As the name suggests internal defects occur inside the weld body and external weld occurs on the weld surface. The most commonly occurring welding defects are lack of fusion, slag inclusion, undercutting, porosity and weld crack (Mandal, 2017).

Traditional way of detecting the welding defects has been inspection by an experienced person. The traditional method has one severe limitation and that is we cannot inspect the inner regions of weld joints without breaking the joint. If we have to break the joint every time then it will be very costly and time consuming, so to overcome this we have nondestructive testing. As NDT techniques use electromagnetic radiation, sound etc, so we are able to inspect the specimens without breaking it and this saves us lot of cost and time. Most frequently used NDT techniques are eddy current, ultrasonic, liquid penetrant, radiographic, magnetic particle (*Nondestructive Testing - Wikipedia, n.d.*).

Both human inspection and NDT techniques have human involvement. Human inspection as the name suggests involves a person, so issues like human error, lack of experience and working in dangerous environment are some of the limiting factors. In case of NDT we need experienced person to analyse the data so lack of experience and human errors can be limiting factors here as well. All these issues can be overcome by involvement of artificial intelligence in both these techniques. In case of human inspection we can use AI to inspect the welding joint and for NDT we can use AI to analyze the data which we get from these techniques. Technological advancements in field of computation and generation of lot of data due to advent of internet have made mass scale use of AI possible. Now we have lot of state of the art (SOTA) deep learning algorithms which perform better than the humans in many fields. Our task of welding defect detection is primarily related to computer vision field of AI. New state of the art techniques in computer vision like YOLO, R-CNN, SSD are some of those techniques which are used in these tasks.

While doing welding surface defect detection speed of detection can be important specially if we are doing real time

defect detection. The deep learning techniques which we mentioned above vary in their speed of the detection, not all of those techniques are suitable for real time detection tasks. Techniques like YOLO, SSD etc are suitable for real time detection tasks while R-CNN is slow technique so we do not use it for real time detection tasks. Reason behind variation in their detection speed is that R-CNN is a two stage detection technique while rest two are single stage detection technique. The two stage detector first selects those regions in the image where chances of finding the object are high, it uses region proposal network to achieve this and after this the localization and classification algorithm is run on those selected regions to detect the objects. We can see that this algorithm is using two stages or two steps to perform full object detection. The single stage detector divides the image into $n \times n$ grid and then performs the localization and classification technique on each of those grid cells in single stage. So in single stage there is no step for selecting regions as classification and localization algorithm is being applied on the whole image. As single stage detector does whole detection task in single stage so it is very fast. But issue is that single stage detectors are little less accurate in comparison to two stage detectors. The loss in accuracy is not that much so we can say that single stage detectors maintain good balance between accuracy and speed. We have two single stage detectors YOLO and SSD and out of these two we choose YOLO as SSD performs poorly while doing detection of small sized images. Welding defects like spatter and porosity are small size objects so using SSD can decrease accuracy of detection.

Fullform of YOLO is You Only Look Once, as the name suggests we look the image only once for completing our object detection. YOLO does all this by dividing the image in grids. Each grid is then checked for object. We apply object localization and classification algorithm on each grid cell. Before starting the training algorithm we have to do image labelling and in this step we draw a bounding box around our object. We draw bounding box so that we can tell the training algorithm the location and type of the object. It can happen that an object is spread across multiple grid cells in that case the grid cell which has mid point of the object we assume that particular grid cell has the object. When prediction is done then each bounding box can have multiple prediction bounding box. We have to reduce the number of prediction bounding box and bring to their number to one. We use non max suppression technique for achieving this.

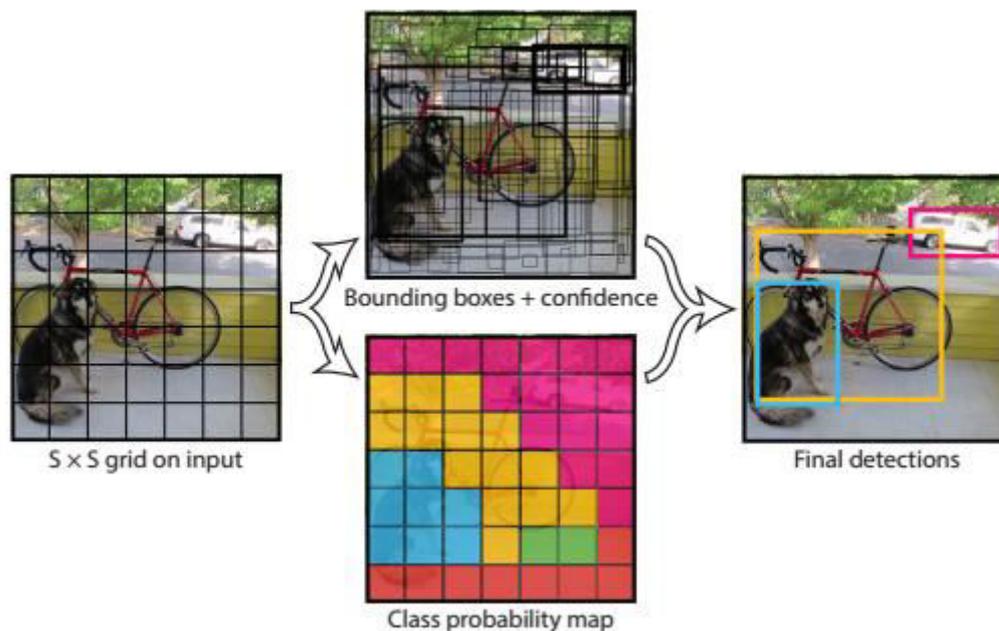


Figure 1: Flow diagram showing steps involved in YOLO algorithm (Redmon et al., 2015)

In above figure the final prediction step's image has single prediction bounding box for each object. This happens with the help of non max suppression.

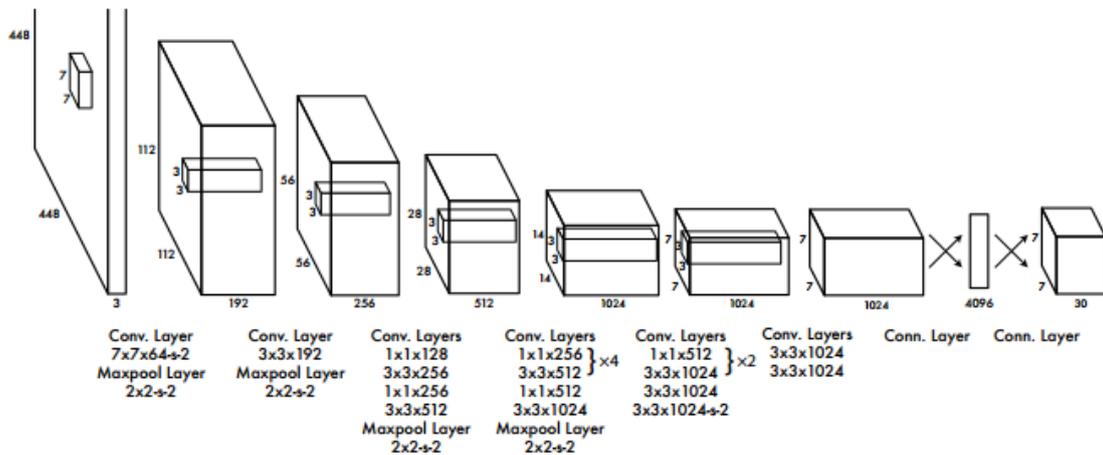


Figure 2: Architecture of YOLOv1 (Redmon et al., 2015)

YOLOv1 is the first algorithm in YOLO family of algorithms. It was proposed in 2015 by Joseph Redmon (Redmon et al., 2015). As shown in the above diagram, the YOLOv1 model has 24 convolutional layers, and after that, we have 2 fully connected layers. The pretraining of the YOLOv1 model has been done on the ImageNet 1000 class competition dataset, and for evaluation, we use the Pascal VOC detection dataset. For training purposes, the image size used is 224x224, but when we go for detection, the image size is doubled (Redmon et al., 2015).

The initial YOLO model has some limitations, and for this reason, there were newer versions of YOLO which improved on the previous versions. For this paper, we are using YOLOv8s, which is one of the latest YOLO models.

II. LITERATURE REVIEW

Survey of research papers related to losses from welding defects tells us how destructive accidents occurred because of weld failures. There was an accident in Hubei province in China, an explosion occurred in Dangyang power plant in 2016, 22 people lost their lives in that accident. (Fu et al., 2018) has done analysis of the accident. The main cause of the accident was a weld crack which had developed in the flowmeter. There was leakage in the plant one day before the accident, but no one paid much attention to that leakage. Another accident occurred in 1980 in the North Sea, the Alexander Kielland semi-submersible drilling rig capsized and it killed 123 people (Alexander L. Kielland (Platform) - Wikipedia, n.d.). (Naess et al., 1982) has done investigation in this accident and found out that the accident was caused because of a fatigue crack which started from a double fillet weld. There were some partial cracks in the welds earlier as well due to poor welding. We can see one thing in both the cases that if weld defects would have been detected earlier, then these accidents would not have happened.

There are some surveys related to types of weld defects and causes of weld defects, which of the weld defects are most commonly occurring. (Kah et al., 2015) discusses about welding defects in friction stir welding, it discusses about the relationship between the weld defects and friction stir welding parameters. It also discusses about the formation and prevention of defects in stir welding. Then it discusses about how metallurgical aspects of weld metal help in the creation of defects. (Chen et al., 2006) has tried to find out how welding defects are formed in 5456 Aluminium alloy in the friction stir welding process. Weld defects were analysed using optical microscopy, energy dispersive X-ray spectroscopy. They found out that a change in the tool tilt angle can result in the generation of defects. (Mandal, 2017) has done a general survey on welding defects, what are the causes and how can we prevent their occurrence etc.

We can use computer vision in various tasks in welding. We can use it for defect detection, detection of weld beads, for monitoring the weld joints etc. We can use two-stage detectors or single-stage detectors as well. (Oh et al., 2020) has used Faster RCNN for defect detection from radiographic testing images of weld joints. (Zou et al., 2021) uses an improved SSD detector for weld seam detection. The YOLO model is also used for many tasks in the field of welding. (Mo et al., 2019) is doing the task of identification and detection of automotive door panel solder joints, and for this, it has used the YOLO3 model. (Zuo et al., 2021) is doing defect detection on the welding surface, and for this, the YOLO series models are

being used. Sometimes improvement is done in normal models so that they can cater to the demands of the problem, same has been done in case of (M. Liu et al., 2023). This paper uses LF-YOLO also called as Lighter and Faster YOLO to detect the weld defect from X-ray images of weld joints. In this paper they have used RMF module. This module has been created to implement both parameter free and parameter based multiscale feature extracting operations. (Lv et al., 2021) has done comparative analysis between improved version of YOLOv3 and normal YOLOv3. They have used these models for surface defect detections on car door seals. We can even use computer vision models for monitoring of our systems or structures. (Y. Liu et al., 2020) has used YOLOv3 for monitoring of rail thermite welded joints. It is important that there should be monitoring of railway thermite weld joints and detection of defects if and when they occur as this will be helpful in improving structural integrity of the railway system.

In this section we saw how important it is for us to have timely detection of the welding defects and we also saw that there is good research related to application of computer vision in welding. But we could not see many papers related to application of latest YOLO models in welding defect detection. So this is the reason behind conducting this research and using YOLOv8s as our algorithm in this paper.

Model details

We have seen basic details about YOLO and YOLOv1 version in introduction part so here we will talk about the YOLOv8 version. This is the same version which we are using in this paper.

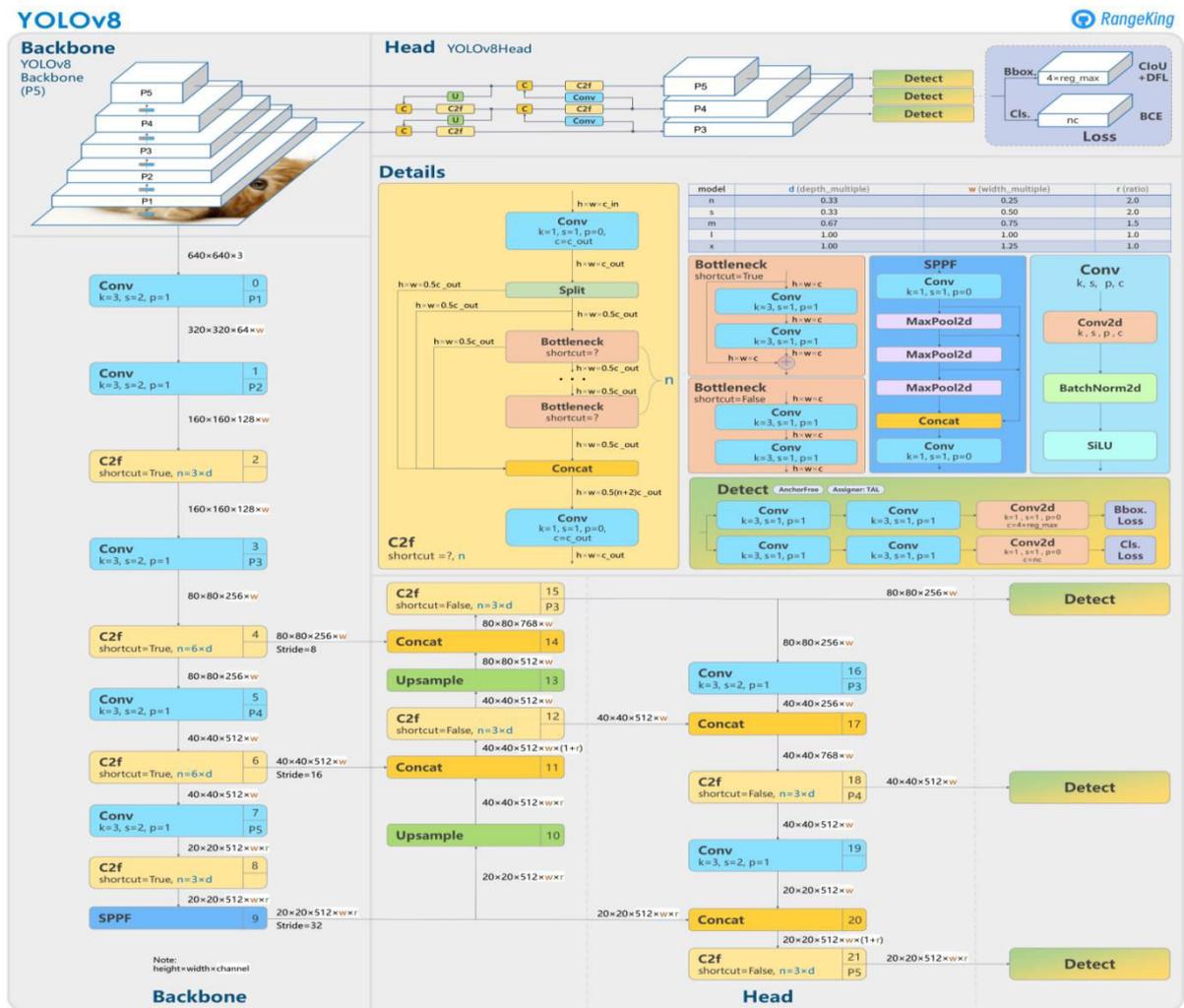


Figure 3: Architecture of YOLOv8 (Brief Summary of YOLOv8 Model Structure, n.d.)

Like most other YOLO algorithms this YOLO algorithm also has 3 parts, backbone, head and neck. Backbone has job of extracting features from the image, the job of head is doing final predictions and neck connects head with backbone. In case of YOLOv8 we have advanced backbone and neck architecture and because of this reason there is improvement in feature extraction and object detection. YOLOv8s has anchor free head which helps in achieving better accuracy and more efficiency. (YOLOv8, n.d.). The anchor free approach which YOLOv8 uses this helps in reducing the number of prediction bounding boxes and because of this the non max suppression step gets finished in much lesser time. (Solawetz & Francesco, n.d.)

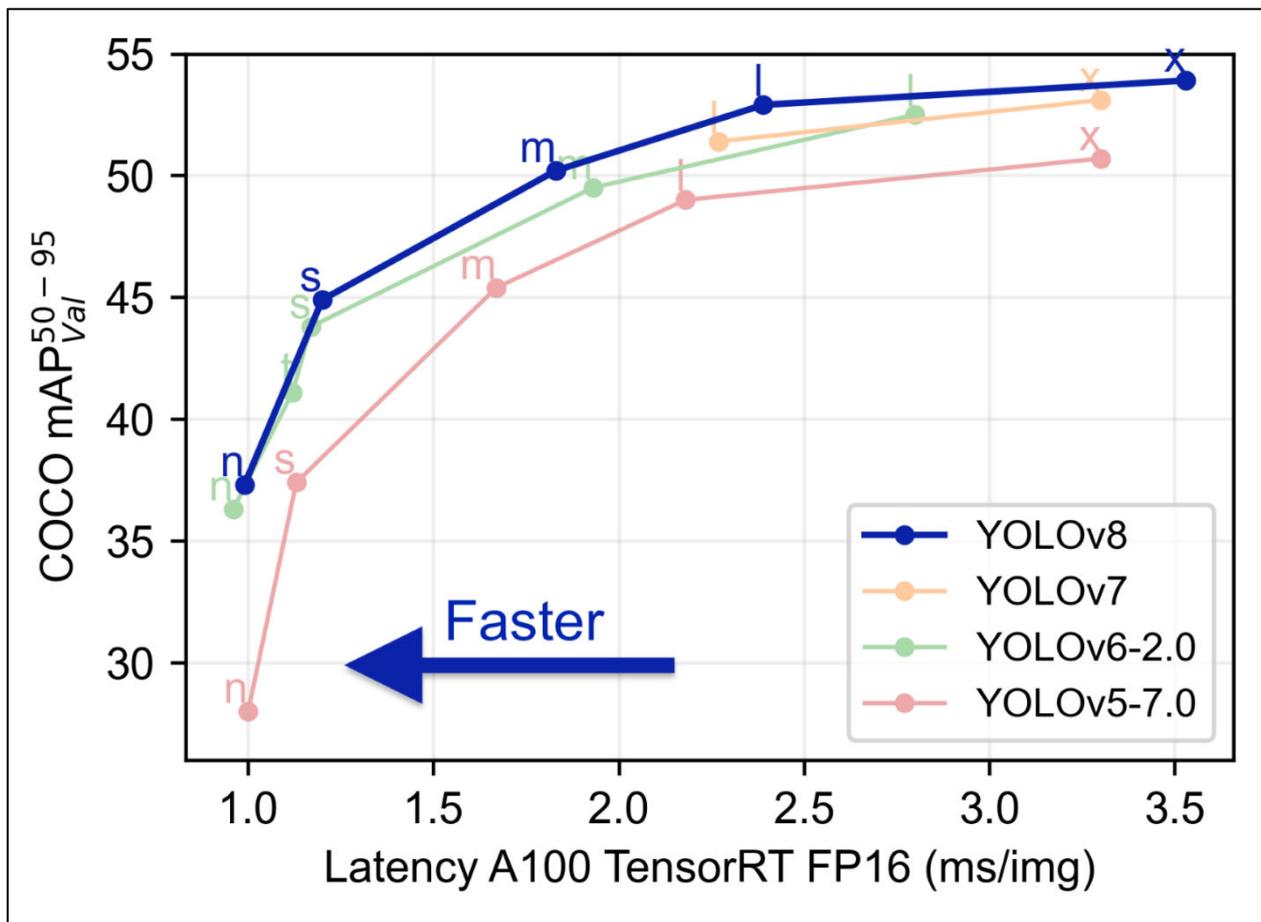


Figure 4: Comparison of YOLOv8 with other YOLO algorithms (YOLOv8, n.d.)

In the above figure we can see many types of YOLOv8 versions are being compared with corresponding types of other older YOLO versions. We have YOLOv8n and corresponding older YOLO versions then we have YOLOv8s and so on. We can see that YOLOv8 algorithm is performing better than rest of the YOLO models, it is faster and has better accuracy. When we increase the size of the model then we can see its accuracy increases and speed decreases but in those cases as well the YOLOv8 model is better than the corresponding versions of other YOLOs.

III. EXPERIMENT DETAILS

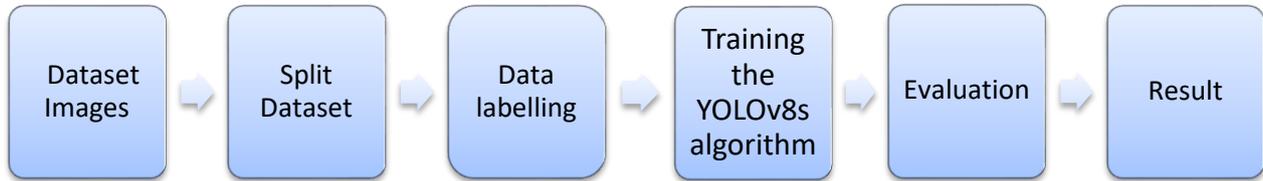


Figure 5: Experimental Flow(Naftali et al., 2022)

(a) Dataset Details:

For this paper we are using welding defect images. Defects which these images have are Porosity and Spatter defects. Total number of images which we have are 30 out of which 25 are for training the model, 3 are for validation step and rest 2 are for testing the model. Each of these 30 images have multiple porosity and/or spatter defects.

(b) Training details:

We have to do the data labelling before training the YOLOv8s model and this has been shown in above shown experimental flow diagram. We do data labelling on makesense.ai website and then for training we use Kaggle website of google. We are using Tesla P1000 GPU for training the model.

While training the model we have to provide values for some of the parameters, for this training those parameters were number of epochs, input image size, batch size. We have trained the model for 500 epochs, input size is 640x640 and the batch size is 8.

We trained the model for 500 epochs but model stopped training at epoch = 350 and best results were achieved at epoch = 250.

(c) Performance metrics:

Analysis of performance of our model is done with the help of performance metrics. For object detection models we pay attention to performance metrics like mAP score, Precision score, Recall score and F1 score.

Precision	$TP / (TP + FP)$
Recall	$TP / (TP + FN)$
F1 score	$2 * Precision * Recall / (Precision + Recall)$
mAP score	$\frac{1}{n} \sum_{k=1}^{k=n} AP_k$

Where TP is True positive, FP is False positive and FN is False negative. AP means Average precision.

IV. RESULTS AND DISCUSSION

We had various steps in the whole procedure, output of those steps were best model which we use for detection purposes, graphs, performance metric values, predicted images from test step. We will discuss about all these things here.

Measure	YOLOv8s
Precision	0.770
Recall	0.613
F1 score	0.682
mAP@0.50	0.714
mAP@0.50:0.95	0.282

Table 1: Performance metrics data for YOLOv8s algorithm

We can see the values of various performance metrics for our model. These values are for the best epoch which was epoch = 250.

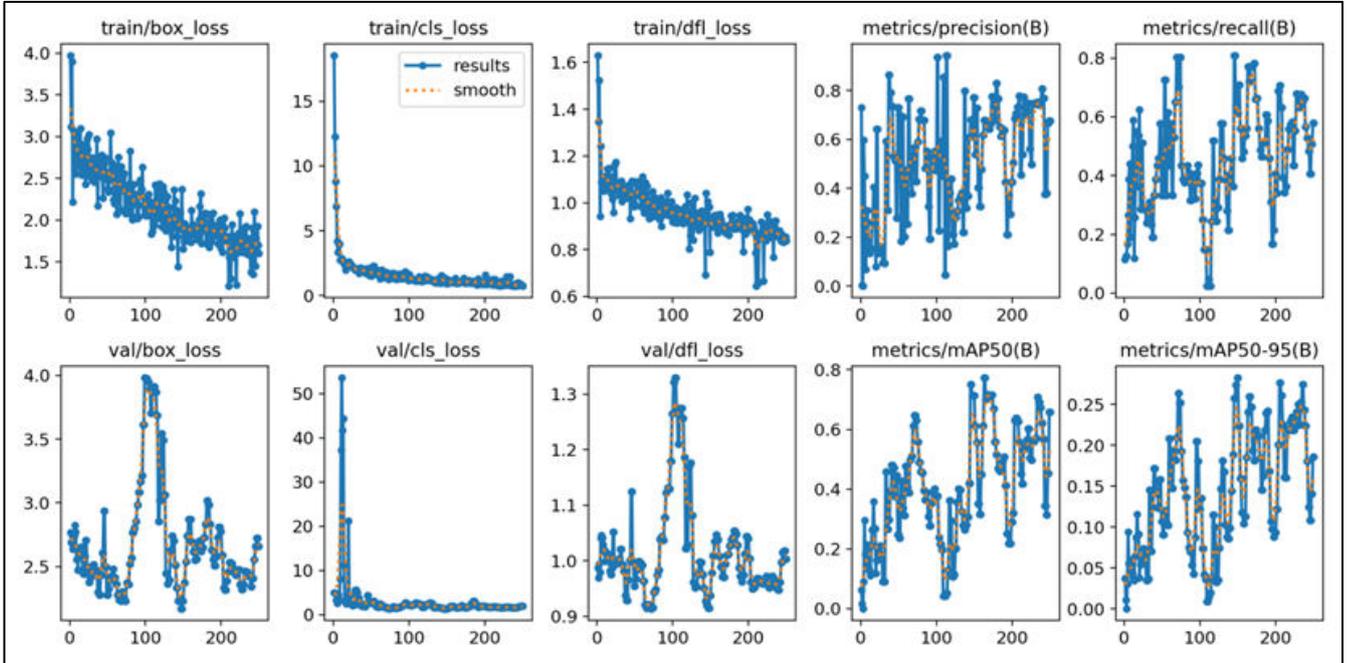


Figure 6: Change in performance metric values and loss values with number of epochs for YOLOv8s model

If we see plots in above figure then we can see that most of the losses are smoothly decreasing with the number of epochs while there is large variation in metrics score plots with epochs.

After training the model we used the best model for doing prediction on our test images, we got following output:



Figure 7(a)



Figure 7(b)

Figure 7(a) and 7(b) are the predicted test images. We can see in above predicted images that except for some of the small sized spatters our model has been able to identify almost all the spatter. The 2nd predicted image shows that our model is doing excellent job in identifying the porosity defects.

V. CONCLUSION

Applications of AI in the field of mechanical engineering are immense. Through this paper we have tried to put light on one of those applications. We have trained one of the latest YOLO model the YOLOv8s model and have used this trained model to the prediction on some of the images and the results are excellent. Model has done has excellent job in detection of both the defects. There have been some issues with spatter defect detection but reason behind that is not having large dataset. Further work can be done by increasing the number of images in dataset and having more defects in those images. This will allow model to detect large variety of defects.

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